Proof of Concept: Fuel Mapping CFFDRSv2.0 Prototype

CabinGIS

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Contents

Action

Running with some of the momentum from meeting 24th Feb, the following was drafted as a quick and dirty pipeline prototype to produce two mapping deliverables described in the NRC grant "High-Resolution Mapping":

- NRC Grant: https://www.ic.gc.ca/eic/site/101.nsf/eng/00157.html

We've since found some relevant R-tools that were developed by NRC in the new cffdrs R-package specifically for generating the two main components of the Canadian Forest Fire Danger Rating System: the Fire Weather Index and the Fire Prediction Behaviour Model. These include algorithms to measure three forest fuels classes and their moisture content indices: Fine Fuel Moisture Code (FFMC), Duff Moisture Code (DMC), Drought Code (DC). FFMC and DMC make up two of the five predictors needed to run the Wotton and Beverly's stand-adjusted fuel-typing model (Wotton and Beverly (2007)). Need a second opinion here as it doesn't seem 100% clear if NRC are interested in vegetation mapping outputs that are focused solely on fuel typing without the moisture codes and climate variables, or they want something that includes the FFMC and DMC.

If its the former, there is some useful info found in the cffdrs package that describe the data requirements of the FWI System There is also a FWI test dataset 'test_fwi' showing the format of these inputs that is presented below. In the pilot test below, we generated the five raster predictors that are required inputs in the Wotton standjust CFFDRS model. These rasters were derived for the Peachland watershed area for the 2021 fire season period up until June 30th of that year.

```
library(cffdrs)
print(as_tibble(test_fwi), n = 10)
```

```
## # A tibble: 48 x 9
##     long   lat    yr   mon   day  temp    rh    ws  prec
##    <int> <int> <int> <int> <int> <dbl> <int> <int> <dbl>
##  1  -100    40  1985     4    13  17       42    25   0
```

```
## 2 -100 40 1985 4 14 20 21 25 2.4
## 3 -100 40 1985 4 15 8.5 40 17 0
## 4 -100 40 1985 4 16 6.5 25 6 0
## 5 -100 40 1985 4 17 13 34 24 0
## 6 -100 40 1985 4 18 6 40 22 0.4
## 7 -100 40 1985 4 19 5.5 52 6 0
## 8 -100 40 1985 4 20 8.5 46 16 0
## 9 -100 40 1985 4 21 9.5 54 20 0
## 10 -100 40 1985 4 22 7 93 14 9
## # ... with 38 more rows
```

However, if its the second, and they are wanting a deliverable that is purely fuel-type focused, it may be worth having at look at and following closely the 'FLNRO 2015 BC Fuel-Typing and VRI-Layering Framework' (Perrakis, Eade, and Hicks (2018)). In it, they've developed an Arc-Python based algorithm that filters the VRI dataset using a kind of multi-criteria classification key to delineate landscapes into polygons according to the 16 Canadian Standard Fuel Type classes (Hirsch (1996)). In the final section below, we made a rough attempt of fitting this algorithm and coding the 100-plus VRI-criteria-layers (only got to 23) to generate similar fuel-type rasters. This report, its scripts and its virtual environment are stored in the github repo here: https://github.com/seamusrobertmurphy/Wildfire-Fuel-Mapping-CFFDRS-2.0.

1 Stand-Adjusted CFFDRS Fuel Typing Model (Wooton & Beverly, 2007)

Five spatial predictor variables are needed to fit the Wotton and Beverly stand-adjusted fuel typing model: "FFMC, DMC, stand (1:5; deciduous, Douglas-fir, mixedwood, pine, spruce), density (1:3; light, mod, dense), season (1, 1.5, 2, 3; spring, spr-sum transition, sum, fall). Two of these predictors, including density and stand were extracted from VRI-layers as simpleFeatures objects and then rasterized and stacked using the terra and raster packages.

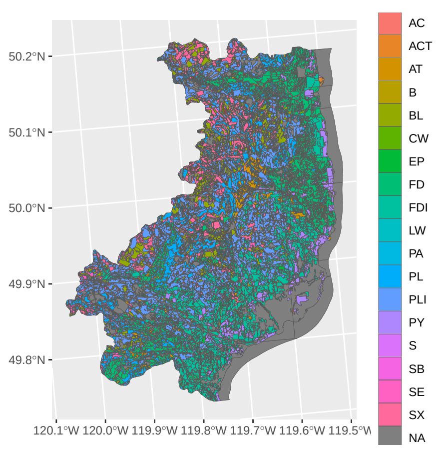
```r
library(ggplot2)
watershed_bdrys = read_sf("./Data/BCGW_7113060B_1645786298548_3276/LWADM_WATMGMT_PREC_AREA_SVW/LWADM_PA
peachland = watershed_bdrys[watershed_bdrys$PRECNC_NAM == "Peachland", ]
vri_sf = read_sf("./Data/BCGW_7113060B_1645786298548_3276/VEG_COMP_LYR_R1_POLY/VEG_R1_PLY_polygon.shp")
vri_sf = st_intersection(st_make_valid(vri_sf), peachland)

stand = vri_sf["SPEC_CD_1"] %>%
  mutate(SPEC_CD_1 = as.factor(SPEC_CD_1))
stand = rename(stand, stand = SPEC_CD_1)
summary.factor(stand$stand)
```

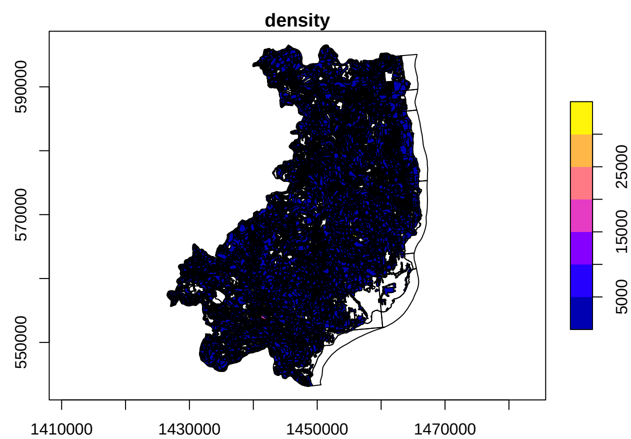
```
##   AC  ACT   AT    B   BL   CW   EP   FD  FDI   LW   PA   PL  PLI   PY    S   SB
##    1   33  496    4 1122    9  104 2255 1648   20   10 1804 1752  299   60    1
##   SE   SX NA's
##  214 1349  875
```

```r
density = vri_sf["LIVE_STEMS"] %>%
  mutate(LIVE_STEMS = as.numeric(LIVE_STEMS))
density = rename(density, density = LIVE_STEMS)
summary(density)
```

```
##     density                    geometry
##  Min.   :    0.0   MULTIPOLYGON :   98
##  1st Qu.:  413.0   POLYGON      :11958
##  Median :  740.0   epsg:3005    :    0
##  Mean   :  982.8   +proj=aea ...:    0
##  3rd Qu.: 1116.0
##  Max.   :30820.0
##  NA's   :812
```

```
#species_palette = "R3"
ggplot(stand) + geom_sf(aes(fill=stand), size = 0.05)


#ggplot(data = sdcounty) +
 # geom_sf(aes(fill = stand), size = 0.25) +
#  scale_fill_distiller(name="Stand Type",
            #           palette = "YlGn",
             #          breaks = pretty_breaks()) +
 # theme_bw() +


#plot(stand[,1], axes=TRUE, cex=0.001)
plot(density[,1], axes=TRUE)
```



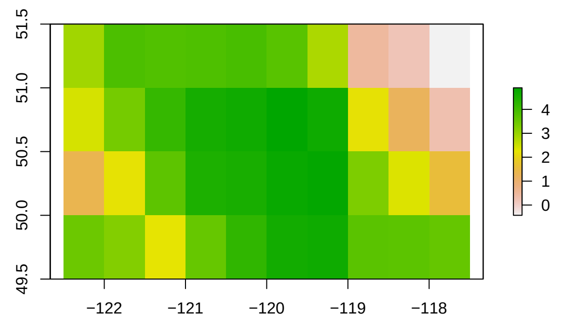


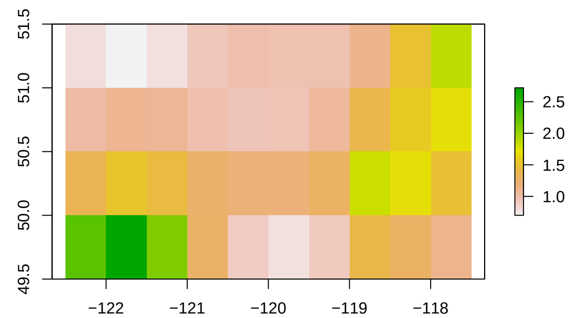
To derive FFMC and DMC rasters we needed to process four climatic rasters representing mean daily conditions since the start of fire season (first day of mean daily temperature above 12C) to June 30th for: 1) mean daily temperature at 2m, 2) mean daily precipitation, 3) mean relative humidity, 4) and mean wind speed at 10m. Climatic rasters were download as NetCDF files from NASA Power platform and imported directly as rasters from their .nc extensive format. The NASA Power platform also provides nice, user-friendly API data source links that would be ideal for this kind of software and grant deliverable

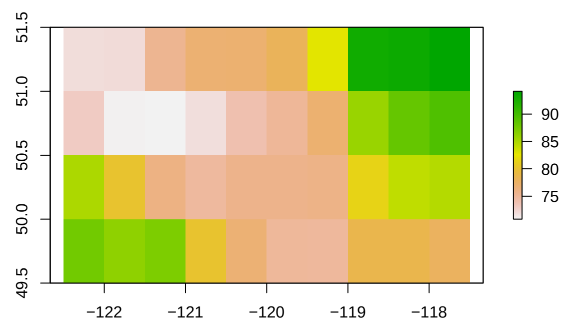
- NASA Power Platform: https://power.larc.nasa.gov/data-access-viewer/

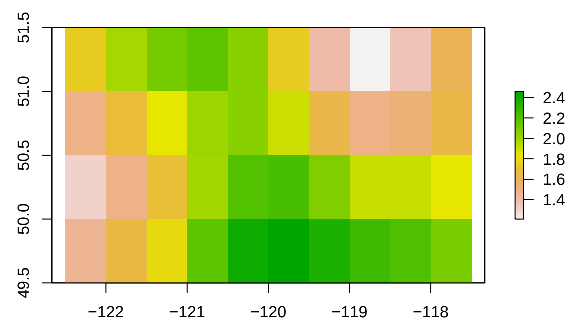
```
temp = raster::raster("./Data/temp.nc")
prec = raster::raster("./Data/prec.nc")
rh = raster::raster("./Data/rh.nc")
ws = raster::raster("./Data/ws.nc")

names(temp) = 'temp'
```

```
names(prec) = 'prec'
names(rh) = 'rh'
names(ws) = 'ws'

plot(temp)
plot(prec)
plot(rh)
plot(ws)
```



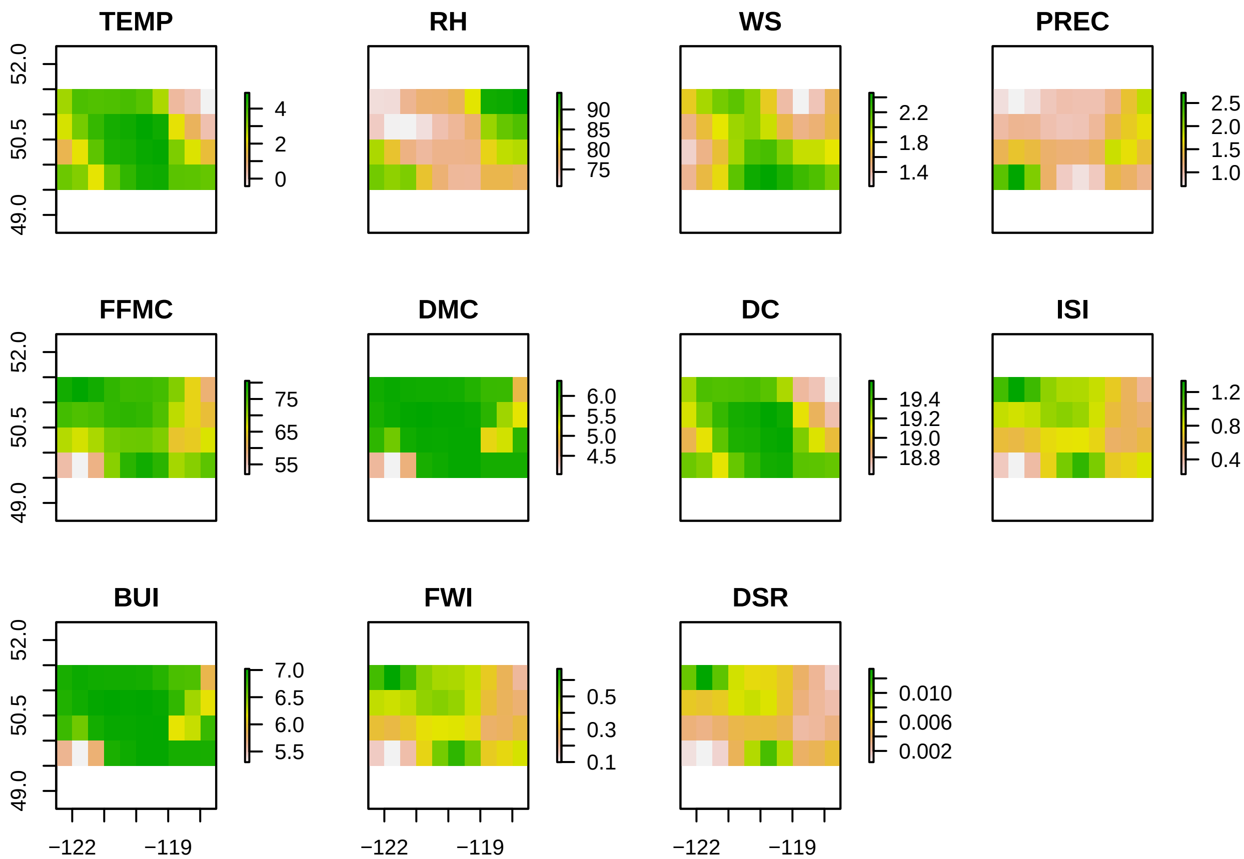






Interpolated climate predictors were assembled as a raster stack and inputted to the fwiRaster function in the cffdrs package. 'out="all"' was selected to produce raster outputs for the three FWI fuel moisture indices of Fine Fuel Moisture Code (FFMC), Duff Moisture Code (DMC), Drought Code (DC), as well as raster outputs for Initial Spread Index (isi), Build-up Index (bui), Fire Weather Index (fwi), and Danger Severity Rating (dsr).

```
stack = stack(temp, rh, ws, prec)
fwi_outputs = fwiRaster(stack, out = "all")
plot(fwi_outputs)
```




```
ffmc = raster(fwi_outputs, layer=5)
dmc = raster(fwi_outputs, layer=6)
dc = raster(fwi_outputs, layer=7)
isi = raster(fwi_outputs, layer=8)
bui = raster(fwi_outputs, layer=9)
fwi = raster(fwi_outputs, layer=10)
dsr = raster(fwi_outputs, layer=11)
```

2 BC WildFire Fuel Typing VRI-Layer Algorithm

The FLNRO 2015 paper provides a really user-friendly screening algorithm of that is design with a hierachy of criteria suited for filtering or subsetting spatial objects in R (although Arc-built). For this, we imported the VRI dataset as a shapefile.shp from the manually downloaded imapBC files and transformed it into a simple feature object and processed it according to the fuel-type criteria checklist using sf, dplyr and terra functions. (*TODO: draft 'spatialPolygonDataFrame' pipeline for any potential future software compatibility issues.*)

```
fields::stats(vri_sf$HRVSTDT)
fields::stats(vri_sf$C_I_CODE)
fields::stats(vri_sf$BEC_ZONE)

#fuel_algo = dplyr::filter(vri_sf, HRVSTDT == NA | HRVSTDT < 2016)
vri_harvest = vri_sf["HRVSTDT"]
wildfire_sf = wildfire_sf["FIRE_YEAR"]
```

```
wildfire_aoi = wildfire_sf$FIRE_YEAR > 2000
wildfire_aoi = st_intersection(st_make_valid(wildfire_sf), aoi_sf)
vri_species_aoi = st_intersection(st_make_valid(vri_species), aoi_sf)
vri_species_aoi$SPEC_CD_1 = as.factor(vri_species_aoi$SPEC_CD_1)
vri_species_aoi =  dplyr::filter(vri_species_aoi, SPEC_CD_1 == "PL" | SPEC_CD_1 == "SB" | SPEC_CD_1 ==
```

TODO: Finish dataframe pipeline below for less buggy inputs with shiny app deploys.

Send to Appendix: Following chunk includes functions for developing dataframe inputs in case of likely software compatability issues.

```
climate_vars = read.csv("./Data/power_nasa_kelowna.csv")
climate_vars_sf = st_as_sf(climate_vars, coords = c("LAT", "LON"), crs = 4326)
raster_template = raster(xmn=49.25, xmx=51.25, ymn=-122.25, ymx=-116.25, res=20, crs = "EPSG:3153")
temp = climate_vars_sf["T2M"]
temp = dplyr::rename(temp, temp = T2M)
temp = rasterize(temp, raster_template, res=20)
rh = climate_vars_sf["RH2M"]
rh = dplyr::rename(rh, rh = RH2M)
rh = rasterize(rh, raster_template, res=20)
ws = climate_vars_sf["WS10M"]
ws = dplyr::rename(ws, ws = WS10M)
ws = rasterize(ws, raster_template, res=20)
prec = climate_vars_sf["PRECTOTCORR"]
prec = dplyr::rename(prec, prec = PRECTOTCORR)
prec = rasterize(prec, raster_template, res=20)
stack = stack(temp, rh, ws, prec)
fwi_outputs_dfpipe = fwiRaster(stack)
```


Hirsch, Kelvin G. 1996. *Canadian Forest Fire Behavior Prediction (FBP) System: User's Guide*. Vol. 7.

Perrakis, Daniel DB, George Eade, and Dana Hicks. 2018. *British Columbia Wildfire Fuel Typing and Fuel Type Layer Description*. Canadian Forest Service, Natural Resources Canada.

Wotton, B Mike, and Jennifer L Beverly. 2007. "Stand-Specific Litter Moisture Content Calibrations for the Canadian Fine Fuel Moisture Code." *International Journal of Wildland Fire* 16 (4): 463–72.